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Procedia Technology 4 (2012) 215 – 219

Procedia
Technology

C3IT-2012

Segmentation and classification of raw arecanuts based on three sigma control limits

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Abstract

Areca nut (*Areca catechu* L.) is one of the important commercial crops in India. There are several computer based technologies for other crops but there is no computer vision based advanced technology in identifying a grade, variety and diseases for an areca nut. In this paper, a novel method is proposed for classification of areca nut into two classes based on color. The proposed method has three steps: (i) Segmentation; (ii) Masking; and (iii) classification. The RGB image is converted into YCBCR color space. Three sigma control limits are used on the YCBCR image for the effective segmentation of areca nuts. Areca nut color space is modelled using three sigma control limits, in which it covers the most significant variation of the color components of the areca nut. The upper and lower limits of the color components are used to segment the areca nut effectively. Classification is done based on the red and green color components of the segmented region of the areca nuts. An experimental result shows the efficiency of the proposed approach.

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Keywords: Segmentation; Classification; Color images; areca nut; three sigma control limits

1. Introduction

Areca nuts play a prominent role in the religious, social and cultural functions and in the economic life of the people in India and it is also called “betel nut” and is used mainly for masticatory purposes. Today, the increasing technological development and sophistication of modern societies impose new quality standards to the crop producers. Consumers demand more and more information about the products they buy, demonstrating clear preferences for well-informed high-quality products. Human has a prominent role in classifying the grades and variety of the areca nuts. There are several computer based technologies for other crops but there is no computer vision based advanced technology in identifying a grade, variety and diseases for an areca nut. There is an increasing demand for computer vision based technology to address the above issues for areca nut farmers.

There have been several techniques proposed for classification of fruits, food and seeds. The literature [1] in the machine vision applications to aquatic foods is grouped under the determination of composition, measurement and evaluation of size and volume, measurement of shape parameters, quantification of the outside or meat color of aquatic foods, and detection of defects during quality evaluation. A robust algorithm for segmenting the food image from a background is presented using color images, this method include: (i)

computation of high contrast grey value image from an optimal linear combination of the RGB color components; (ii) estimation of a global threshold using a statistical approach; and (iii) morphological operation in order to fill the possible holes presented in the segmented binary image [2]. In order to obtain required parameters for detection algorithm and calibration images, physical properties e.g. three mutually perpendicular axes such as major, intermediate and minor mass and volume were measured. The area is computed from the 2D image of watermelon and so an estimate of the watermelon's mass/volume is achieved [3]. The tomato classification by using image processing was proposed [4]. An aspect ratio was used to detect short, medium and tall kiwifruits and another parameter, ellipsoid ratio was used to detect flattened fruits [5]. Geometrical attributes and some physical characteristics of cantaloupe fruit such as length, major diameter, minor diameter, mass, volume and density were measured [6]. Calculating the mean color intensity to differentiate between the different colors or ripeness of the oil palm fruits is proposed [7]. A novel system for grading oranges into three quality bands, based on their surface characteristics like size, shape, surface coloration and defect markings using neural network classifier [8]. Classification of a tomato using fuzzy the mamdani inference, adaptive fuzzy neural network (anfis) methods were used for each of that image [9]. Image analysis system developed to evaluate the color of the stone fruit [10]. Computation of the estimated volume of papaya is simply done by measuring the radius of the object at specific area and integrating over the length. Finally, papaya weights are estimated using the volume information [13]. A study of three important issues of the color pixel classification approach to skin segmentation are color representation, color quantization, and classification algorithm[14]. Designed and implemented a prototypical computer vision based date fruit grading and sorting system based on a set of external quality features using back propagation neural network classifier[15]. An automated grading system for *Jatropha curcas* by using a color histogram method to distinguish the level of ripeness of the fruits based on the color intensity [16].

From the literature survey, we found that classification of Fruits, Flowers, Seeds etc. have been done, to the best of our knowledge, no work has been attempted towards classification of arecanuts using Image processing approach. In this paper, four types of arecanuts are considered. Namely api, bette, mine, and gorublu. For classification problem, the nuts are grouped into only two classes i.e api ,bette and minne belongs to one class called Boiling Nuts (BN) and gorublu belongs to another class called Non Boiling Nuts (NBN). In our approach arecanuts can be classified based on their color component. We have conducted a survey about 15 locations and have got the following observations:

- All the gorublu arecanuts will be in reddish yellow color (Belongs to NBN class).
- All the bette, api and minne are in green color. (belongs to the class BN).
- Nuts which are in transition state(contains 25% of the green color) from bette to gorublu also belong to BN class

2. Proposed Methodology

In this work, arecanuts are classified based on their color components. The RGB image is converted into *YCBCR* color space. The red and blue color components of arecanut objects were cropped manually from the images and determined ucl(upper control limit) and lcl(lower control limit) of the colors using equations(1),(2),(3) and (4), these values are determined empirically.

$$ucl_{cb} = \mu_{cb} + 3\sigma_{cb} \quad (1)$$

$$lcl_{cb} = \mu_{cb} - 3\sigma_{cb} \quad (2)$$

$$ucl_{cr} = \mu_{cr} + 3\sigma_{cr} \quad (3)$$

$$lcl_{cr} = \mu_{cr} - 3\sigma_{cr} \quad (4)$$

Where μ_{cb} and μ_{cr} are the mean intensities for blue and red chroma components respectively and are determined using equations (5) & (6).

$$\mu_{cb} = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N C_B(i, j) \quad (5)$$

$$\mu_{cr} = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N C_R(i, j) \quad (6)$$

Where C_B & C_R are chromatic blue and red color components in the YCBCR color space respectively and i & j are the pixel coordinates in rows M and columns N . σ_{cb} and σ_{cr} are the standard deviation for blue and red chroma components respectively. These values are determined using equations (7) & (8).

$$\sigma_{cb} = \sqrt{\frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (C_B(i, j) - \mu_{cb})^2} \quad (7)$$

$$\sigma_{cr} = \sqrt{\frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N (C_R(i, j) - \mu_{cr})^2} \quad (8)$$

The shadow was removed before segmenting the object in the image. For this task, 3σ control limits [11] are used to set the background color into black, then cluttered background will be removed using equation (9).

$$A(x, y) = \begin{cases} 255, & \text{if } lcl_{cb} < \mu_{cb} < ucl_{cb} \text{ \& } lcl_{cr} < \mu_{cr} < ucl_{cr} \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Where A is the segmented image containing a arecanut regions.

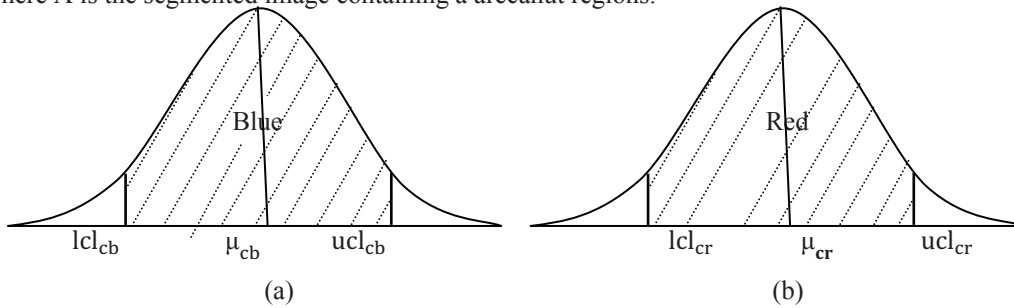


Fig. 1. (a) 3σ control limits for blue chroma component; (b) 3σ control limits for red chroma component

The segmented image is converted into binary image and apply the morphological opening operation [12] in order to remove possible noise outside the arecanut object using equation (10).

$$A \ominus B = (A \ominus B) \oplus B \quad (10)$$

Where A is the segmented binary image and B is the structuring element. In our experiment 4×4 symmetric square structuring element is considered. A hole filling algorithm [12] is applied in order to fill the possible holes inside the arecanut object using equations (11) & (12).

$$X_k = (X_{k-1} \oplus B) \cap A^c \quad k = 1, 2, 3, \dots \quad (11)$$

$$m = X_k \cap A \quad (12)$$

Where $X_0 = p$. The set X_k contains all the filled holes. The set union X_k and A contains all the filled holes and their boundaries. The algorithm is terminated if $X_k = X_{k-1}$. Where B is a symmetric structuring element. After filling the holes, arecanut object in the image mask will be of same shape and size as shown in the original image in fig. 2(c). Multiply the mask with the original image using equation (13), the arecanut object will be segmented as shown in fig. 2(d).

$$f_s = \sum_{i=1}^M \sum_{j=1}^N m(i, j) \times f(x, y) \quad (13)$$

Where f_s , m and f are the segmented, mask and original images respectively.



Fig. 2. Sample Results (a) Bette image; (b) segmented image; (c) filter; (d) segmented color image

Blue component will not participate in forming yellow color, so blue color is completely eliminated from the image using equation(14).

$$\sum_{i=1}^M \sum_{j=1}^N B(i, j) = 0 \quad (14)$$

If the average color of Red (μ_R) is higher than the average color of Green (μ_G) then it is referred to class NBN else it's class BN. μ_R and μ_G is determined using the equation(15) & (16).

$$\mu_R = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N R(i, j) \quad (15)$$

$$\mu_G = \frac{1}{M \times N} \sum_{i=1}^M \sum_{j=1}^N G(i, j) \quad (16)$$

The green component is increased by threshold T for the arecanuts which are in transition state will fall into BN class and red component is decreased by threshold T for the arecanuts which are in transition state will fall into NBN class using equations (17) & (18) respectively.

$$G(x, y) + T \Rightarrow \text{BN Class} \quad (17)$$

$$R(x, y) - T \Rightarrow \text{NBN Class} \quad (18)$$

Where threshold value T is empirically determined based on our dataset considered under analysis. The value of T is 25 in our experiments.

3. Results and Discussion

The most common commercial variety of arecanut is considered for this study. The database contains 629 images from 15 different locations out of which 71 is considered for training and remaining 558 is considered for testing. Images with 3000x4000 pixel resolution were obtained using Canon digital color camera (Power Shot A1100IS). All the Images were taken to approximately fill the camera field of view in natural day light with white background. Images were resized into 150x200 pixel resolution for reasonable computation speed. The proposed method efficiently classify various arecanuts such as api, bette, mine and gorublu into two classes BN and NBN as given in table 1. The misclassification is due to the muddy and damaged nuts.

Table 1. Sample experimental results of the classification in supervised learning and unknown samples.

Class	Samples for testing	Misclassification	Success rate
BN	389	4	98.97
NBN	169	4	97.63

4. Conclusion

In this paper we have used 3σ control limits to segment the arecanuts from the image. In the segmented region, the blue color component is normally suppressed and only red and green components are used to classify the arecanuts. The upper and lower control limits of the blue chroma and red chroma color components are determined using three sigma variations from the mean. These control limits are effective enough to

segment the arecanut regions. Further classification is done based on the red and blue color components of the segmented region of the arecanut. Experimental results demonstrated the efficiency of the proposed approach. This method can be extended to other objects such as classification of fruits, seeds, flowers etc. where sorting and quality rating is normally done by experts.

5. Acknowledgement

The authors would like to thank Kuvempu University, Shankaraghatta, Shimoga, Karnataka, India for the support during this work.

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